Convergence of score-based generative modeling for general data distributions

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Abstract

Score-based generative modeling (SGM) has grown to be a hugely successful method for learning to generate samples from complex data distributions such as that of images and audio. It is based on evolving an SDE that transforms white noise into a sample from the learned distribution, using estimates of the score function, or gradient log-pdf. Previous convergence analyses for these methods have suffered either from strong assumptions on the data distribution or exponential dependencies, and hence fail to give efficient guarantees for the multimodal and non-smooth distributions that arise in practice and for which good empirical performance is observed. We consider a popular kind of SGM -- denoising diffusion models -- and give polynomial convergence guarantees for general data distributions, with no assumptions related to functional inequalities or smoothness. Assuming L^2-accurate score estimates, we obtain Wasserstein distance guarantees for any distribution of bounded support or sufficiently decaying tails, as well as TV guarantees for distributions with further smoothness assumptions.